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# **Modelling correlation patterns in mode choice models estimated on multiday travel data**

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## **Abstract**

Understanding individual choices over time and measuring the day-to-day variability in travel choice behaviour is important in transport planning practice. Although not very common, several multi-day travel surveys have been conducted in various parts of the world and panel data is available to model different transport choices. Still an open question is determining the most appropriate length of a panel to allow revealing variability in travel behaviour (in particular mode choice). In addition, no agreement has been reached about modelling the various dimensions of correlation over repeated observations. In this paper, we use the six-week panel dataset from the Mobidrive survey to estimate mode choice models that account for correlation across individual observations over two time-periods: all days of a single week and different days of the week (i.e. all Mondays) in the wave. We first analyse these effects separately, estimating different models for each type of correlation; then we try to disentangle the relative effects of each type of correlation, estimating both types jointly. We find that both types of correlation appear highly significant when estimated alone, while only the correlation across a given day over the six-week period remains significant, when both types are estimated jointly. This implies that for the Mobidrive panel there is less variability in mode choice across weeks than across days of each week. It also suggests that one week could be an appropriate length for a panel in the case of mode choice modelling, allowing to reveal correctly the day-to-day variability in this case.

## 1. Introduction

Transport planners and modellers have often questioned if a one-day dataset allows to capture properly the full range of travel undertaken by an individual, as many activities are not necessarily performed on a daily basis. A related problem is how to measure variability (day-to-day, week-to-week) in travel behaviour. However, although several multi-day (or panel data<sup>1</sup>) travel surveys and advanced modelling techniques to work with them are available; analyses based on these type of data are still not a standard tool for travel behaviour modelling and demand forecasting.

Panel data can be classified into two categories: “long survey panels” and “short survey panels”. The first consists of repeating the same survey (i.e. with the same methodology and design) at “separate” times; for example, once or twice a year, for a certain number of years. Long survey panels have been extensively used in the past to gain insights into activity scheduling and planning, to study dynamic effects, and for their ability to identify temporal variation in travel behaviour (Hanson and Huff, 1988; Jones and Clark, 1988; Pas, 1988; Pas and Sundar, 1997).

The “short survey panels” are, in general, more recent applications and consist of multi-day data where repeated measurements are collected on the same sample of units over a “continuous” period of time (e.g. seven or more successive days), but the survey is not necessarily repeated in subsequent years. In 1999, Axhausen and his group collected a six-week travel survey (called Mobidrive) for the German cities of Karlsruhe and Halle. A similar survey design, improved with the experience gained in Germany, was transferred in 2003 to Thurgau (Switzerland). These panels have been used to detect rhythms of daily life (Axhausen *et al.*, 2002), to compare different indices that measure similarities of travel behaviour (Schlich and Axhausen, 2003), to draw evidence on the parametric assumptions behind the value of time distribution (Cirillo and Axhausen, 2006), to examine the length between successive participations in several activity purposes (Bhat *et al.*, 2005), to explain current behaviour on the individuals’ history and experience (Cirillo and Axhausen, 2010), to study the intrinsic variability in individual preferences for mode choice, the effect of long period plans and habitual behaviour in daily mode choices (Cherchi and Cirillo, 2014), to account for the dynamic effect of inertia over time in mode choice (Cherchi *et al.*, 2013) and to study the effect of intra-individual variations in preferences in the estimation of equity effects in the case of congestion charging (Börjesson *et al.*, 2013).

On the other hand, data from Mobidrive and a three-day activity diary collected in Santiago de Chile in 2003, were used by Jara-Díaz *et al.* (2007) to estimate discrete-continuous mode choice and activity duration models. Furthermore, a two-day time-use diary, extracted from the 2002 US National Panel Study of Income Dynamics, was used by Copperman and Bhat (2007) to examine time-use in children’s activities. Using a seven-day diary from the Flemish Time-Use Surveys, Minnen *et al.* (2015) studied transport habits under different delineations of the time-use data and for different assumptions about regularity (i.e. varying its *tempo* and *timing*), while Minnen and Glorieux (2011) discussed the length of the time-use survey in order to capture the organization of individuals along cycles of work and leisure.

A Computerized Household Activity-Scheduling Survey (CHASE) was designed in Toronto (Canada), applied over a period of seven days (Doherty and Miller, 2004) and used to estimate a demand model system for daily activity programming (Khandker and Miller,

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<sup>1</sup> In this paper we use the term “panel data” to indicate a typical revealed preference survey repeated several times (strictly speaking, repeated data from a stated preference survey could also be considered a panel).

2007). Stopher *et al.* (2007) pioneered the use of Global Positioning Systems (GPS) as a means of measuring personal travel; they used a 28-day GPS survey of 50 households to analyse the variability in daily travel of individuals and the proportions of variance due to intrapersonal and interpersonal variability. Finally, Vanhulsel *et al.* (2007) introduced an extended reinforcement learning approach to produce weekly activity patterns in Belgium.

The *Santiago Panel* (2006- 2010) combined both “short” and “long” survey panel approaches (Yañez *et al.*, 2010), as it was a five-day pseudo diary that was repeated five different times, just before and four times after the implementation of the radically new Santiago’s public transport system, Muñoz *et al.*, 2009). Data from this panel have been used to study the effect of shock and inertia in individual behaviour and to examine the effect of repeated observations (Yañez *et al.*, 2008) and, more recently, to study the evolution and persistence of modality styles and travel mode choice behaviour in a dynamic context (Vij, 2013).

In an Asian context, the National Planning and Development Agency of the Republic of Indonesia and the Japan International Cooperation Agency collected SITRAMP in 2004. It consists of an activity diary survey for respondents from households within the Jakarta Metropolitan Area in two consecutive weekdays, Thursday and Friday, and two consecutive weekend days, Saturday and Sunday; this dataset was used to study day-to-day variability in travellers’ activity-travel patterns (Dharmowijoyo *et al.*, 2016). A multi-dimensional three-week household time-use and activity diary was collected in the Bandung Metropolitan Area, Indonesia. Preliminary analyses have been conducted to examine the use of motorised modes, activity participation and multi-tasking, and the relation between transport choices and physical health (Dharmowijoyo *et al.*, 2015).

Although this literature review is not exhaustive by any means, it clearly shows that the use of panel data, especially short survey panels, has recently increased. Nevertheless, the applications mainly refer to time-use, activity choice and activity duration, while estimation of mode choice models with panel data has received less attention. Another topical element in the recent literature is the importance of day-to-day variability and the correct length of a panel to allow revealing or avoiding such variability. In particular, a number of questions related to modal choice are still open. Do individual mode choices differ among days of the same week? Do they differ among weeks? Do we really need to have information on several weeks to capture individual behaviour dynamics?

There are several ways these problems can be addressed. Properly accounting for the various dimensions of correlation over the repeated observations provided by a given individual is crucial to understand the long-term structure of individual choices and should give insights into the proper length of the survey. It should also allow to correctly estimating models and properly use them in prediction. In this context, the use of short survey panels appears fundamental as several dimensions of correlation across responses can be studied, i.e. over trips made the same day, the same week, a given day-of-week in a longer period, and/or over individuals and households.

In this paper, we use the six-week Mobidrive panel data to estimate mode choice models that account for correlation across individuals over two time-periods: a single week and a day of the week (i.e. all Mondays) in the whole panel. We first analyse these effects separately, estimating different models for each type of correlation. However, in that case it is not possible to ascertain their relative effects over different time-periods. To overcome this problem, we then made the important step forward of trying to disentangle the relative effects of each type of correlation. A flexible model that jointly accounts for both dimensions of correlation is estimated, allowing for a direct comparison of their relative effects. As in

Cherchi and Cirillo (2014), and differently from the majority of modal choice models reported in the literature, we study the sequence of mode choices at the tour level (i.e. the sequence of trips performed by an individual, starting from a given base - home or workplace - and ending at the same base). Tours and sequences of tours, allow the analysis of dependence among trips, the temporal organization (scheduling) of activities and the distinction between tours that involve one or multiple stops.

The rest of the paper is organized as follows. In Section 2 we discuss the issue of modelling with panel data and how to account for correlation across the observations provided by a given individual. We first discuss the general theory and then how we extend it to disentangle the relative effects of the two levels of correlation considered in the paper: (1) over a single week and (2) over days of the week. Section 3 provides a brief description of the dataset used and a descriptive analysis of some characteristics of the panel data sample. Section 4 reports our modelling estimation results, and Section 5 summarizes our conclusions.

## 2. Mixed Logit model on panel data: accounting for correlation across individuals

The Mixed Logit (ML) is any model the choice probability of which can be expressed as an integral of standard logit probabilities, evaluated at a vector of unobserved components  $\mu$ , over a density of parameters (Train, 2009). The ML model, in fact, allows for a very rich decomposition of the vector of unobserved components (Greene and Hensher, 2007); in particular, it allows for correlation within individuals, which is the typical effect that occurs in panel data where each individual provides more than one piece of information. In these cases, the utility ( $U_{qjt}$ ) that individual  $q$  associates with alternative  $j$  on choice situation  $t$ ; has the following structure:

$$U_{qj_t} = (b_k + \mu_{qk}) X_{kqj_t} + [\dots] + \varepsilon_{qj_t} \quad (1)$$

where  $X_{kqj_t}$  is the  $k_{th}$  attribute in choice situation  $t$  ( $X$  might also be an alternative specific constant<sup>2</sup>) the parameter of which shows random heterogeneity; As well known, the vector  $\mu$  in the ML model can assume any desired distribution. We made the assumption that the random term distributed Normal  $(0,1)^3$ , hence it was  $\mu_{qk} = \nu_{qk} \sigma_k$  where  $b_k$  and  $\sigma_k$  are the mean and standard deviation of the  $k_{th}$  random parameter, while  $\nu_{qk}$  is a random variable that varies among individuals but is fixed across the choices of the sequence  $\mathbf{j}$ , and accounts for correlation across the  $T$  choices of each individual. For simplicity we only show one random parameter but, as well known, equation (1) can be extended to account for almost any number of random parameters as well as for correlation among them. Finally  $\varepsilon_{qj_t}$  is the typical additive extreme value type 1 (EV1) error, which generates the standard logit probability.

Following Train (2009), if  $\mathbf{j} = \{j_1, \dots, j_t, \dots, j_T\}$  is the sequence of choices made by each individual  $q$ , the probability ( $P_{qj}$ ) of person  $q$  making this sequence of choices is the product

<sup>2</sup> Although both versions of the ML (random parameter and error components) can be used to account for differences between long and short-term variations, the error components specification carries some more risks in complex structures due to theoretical identification problems (Walker, 2002).

<sup>3</sup> This assumption does not impose any restrictions on the methodology proposed and several other distributions can be used, from simple distributions such as the triangular to more flexible, but also more complex, forms such as the  $S_B$  distribution (Train and Sonnier, 2005). Some important advantages of using the Normal distribution are discussed by Sillano and Ortúzar (2005).

of the conditional logit formula, integrated over the density of the parameters; as well known too, the logit formula itself is the exact integral of the density function of iid EV1 variables (Ortúzar and Willumsen, 2001, Chapter 7). In particular, from equation (1) the density function of  $\varepsilon_{qj_t}$  is conditional upon the realization of  $v_{qk}$ ; hence for a given person  $q$ , the probability of making the sequence of choices  $\mathbf{j} = \{j_1, \dots, j_t, \dots, j_T\}$  can be written as:

$$P_{qj} = \int \int_{R_v R_\varepsilon} f(\boldsymbol{\varepsilon} | v_q) f(v_q) dv_q d\boldsymbol{\varepsilon} \quad (2)$$

where the domains of integration are:

$$R_v = [-\infty, +\infty] ; \quad R_\varepsilon = \begin{cases} \varepsilon_{qj_t} \leq \varepsilon_{qj_t} + (b_k + v_{qk} \sigma_k) (X_{kqj_t} - X_{kqj_t}) + [\dots] & \forall j \in I_q \\ U_{qj_t} \geq 0 \end{cases} \quad (3)$$

Finally, as  $f(\boldsymbol{\varepsilon} | v_q) = f(\varepsilon_{qj_1} | v_q) \cdot \dots \cdot f(\varepsilon_{qj_t} | v_q) \cdot \dots \cdot f(\varepsilon_{qj_T} | v_q)$  the probability ( $P_{qj}$ ) takes the typical expression:

$$P_{qj} = \int \prod_{t=1}^T \frac{e^{V_{qj_t}(v_q)}}{\sum_{j \in I_q} e^{V_{qj_t}(v_q)}} f(v_q) dv_q \quad (4)$$

The six-week panel data available to estimate our models includes several dimensions of potential correlation across tour mode choices made during the same day (1), the same week (2), or by the same individual (3). In this paper, we focus on the correlation over a given day in the whole panel and over all days in a single week, with the specific aim of disentangling their relative effects.

Figures 1 and 2 show schematically all the information available for each individual  $q$  and the two different ways in which we chose to investigate correlation. In particular, Figure 1 shows correlation over a given day throughout the weeks, while Figure 2 shows correlation inside each week. Of course, correlation over all observations for each individual in a wave includes all tours reported by that individual.

Figure 1: Correlation over given days of the panel for each individual  $q$

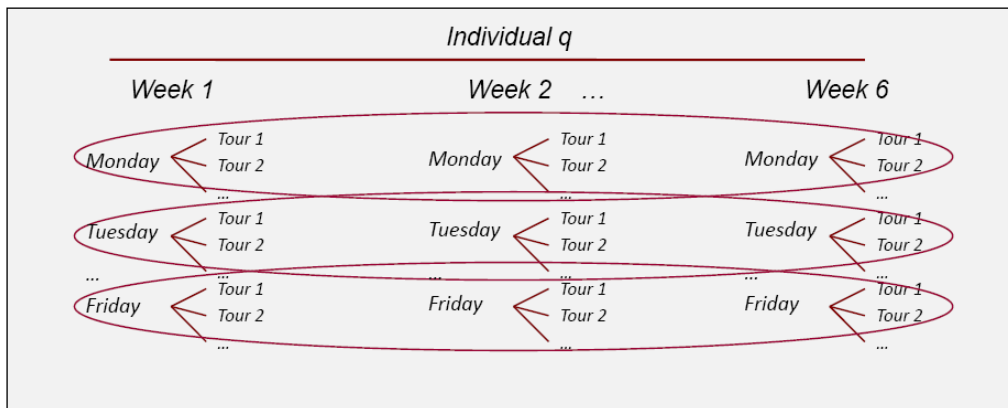
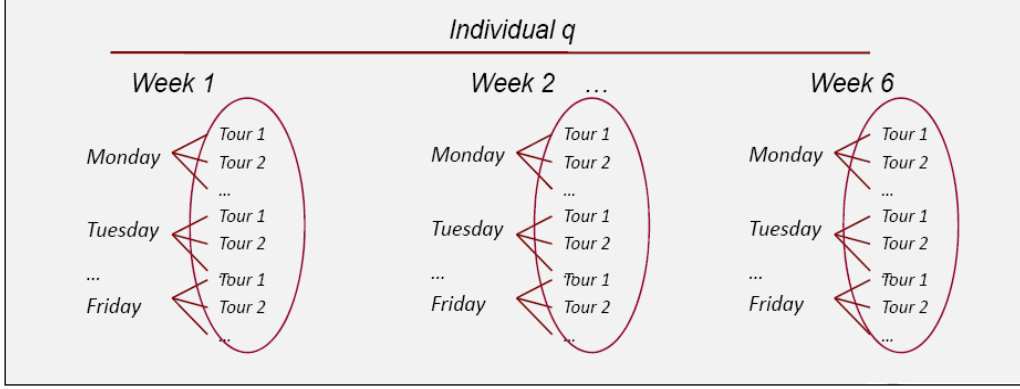


Figure 2: Correlation over each week for each individual  $q$ 

In our case, the sequence of choices made by each individual  $q$  can be written as  $\mathbf{j} = \{j_{\text{monday}, w1}, \dots, j_{d, w}, \dots, j_{\text{friday}, w6}\}$ . If only correlation over each week was considered, the choice sequence for each week  $w_i = \{w_1, \dots, w_6\}$  would be  $\mathbf{j}_{w_i} = \{j_{\text{monday}, w_i}, \dots, j_{d, w_i}, \dots, j_{\text{friday}, w_i}\}$ . Analogously, the sequence of choices for each day (e.g.  $d = \text{Monday}, \text{Tuesday}$ , and so on) over the six weeks would be  $\mathbf{j}_d = \{j_{d, w1}, \dots, j_{d, w2}, \dots, j_{d, w6}\}$ . It is important to note that correlation over days and over weeks can be thought of as “subsets”<sup>4</sup> of the correlation over individuals. In fact, as illustrated in Figure 1, the sequence of choices over days is a subset of the sequence for each individual ( $\mathbf{j}_d \subset \mathbf{j}$ ). Analogously, as illustrated in Figure 2, the sequence of choices over each week is a subset of the sequence for each individual ( $\mathbf{j}_{w_i} \subset \mathbf{j}$ ).

When only one type of correlation is accounted for (i.e. only the correlation for each day over the six weeks) the ML model in equation (4) is the standard formulation for choice sequences (Train, 2009). Instead, when both types of correlation are estimated jointly, new assumptions need to be made because the sequences of choices over days and over each week represent two overlapping but disjoint sets ( $\mathbf{j}_d \not\subset \mathbf{j}_w$ , and  $\mathbf{j}_w \not\subset \mathbf{j}_d$ ).

To jointly estimate these two correlation effects we assumed that attribute tastes were distributed across days and across each week with the same mean ( $b_k$ ) but with different standard deviations across days ( $\sigma_{k1}$ ) and across weeks ( $\sigma_{k2}$ ). The specification of the random terms in equation (1) then can be rewritten as follows:

$$U_{qj_{d,w}} = (b_k + v_{qk,d}\sigma_{k1} + v_{qk,w}\sigma_{k2})X_{kqj_{d,w}} + [\dots] + \varepsilon_{qj_{d,w}} \quad (5)$$

where  $U_{qj_{d,w}}$  is the utility that individual  $q$  associates to alternative  $j$  on the day  $d$  of week  $w$ ;  $X_{kqj_{d,w}}$  is the  $k$ th attribute with a parameter showing random heterogeneity;  $v_{qk,d}$  is a random variable distributed  $N(0,1)$  that varies among individuals and across days but is fixed for the same day across the weeks of the panel (i.e. all *Mondays* and so on). Analogously  $v_{qk,w}$  distributes  $N(0,1)$  and varies among individuals and weeks but is fixed for all days inside each week.

<sup>4</sup> This sentence does not imply that the models are nested from a modelling perspective and should not be confused with that.

For simplicity, equation (5) only reports the specification of the random terms. The final specification adopted to estimate the ML model with our panel data includes also several socio-economic variables (*SE*) with linear and parameterized effects to account for systematic heterogeneity around the preferences for specific alternatives and around the responses to level-of-service attributes (Ortúzar and Willumsen, 2001, page 279). Moreover, equation (5) refers to only one random parameter but, as we discuss in the results, random heterogeneity was tested for both travel time and cost. Hence in our case  $k=1, 2$ . We also tested for correlation between the time and cost parameters but it came out as insignificant.

Finally, in our specification the random term  $\varepsilon_{qj,d,w}$  has, as usual, the typical additive extreme value type 1 (EV1) error, with conditional density function equal to:

$$f(\varepsilon_{qj,d,w} | v_{qk,d}, v_{qk,w}) = \prod_{d=Mon, \dots, Fri} \prod_{w_i=w_1, \dots, w_6} f(\varepsilon_{qj,d,w} | v_{qk,d}, v_{qk,w_i}) \quad (6)$$

Then, the sequence of choices made by individual  $q$  is  $\mathbf{j} = \{j_{monday, w1}, \dots, j_{d,w}, \dots, j_{friday, w6}\}$ , and the probability ( $P_{qj}$ ) of person  $q$  making this choice sequence is:

$$P_{qj} = \int_{R_v} \prod_{d=Mon, \dots, Fri} \prod_{w_i=w_1, \dots, w_6} \frac{e^{V_{qj_i}(v_{k,d}, v_{k,w})}}{\sum_{j \in I_q} e^{V_{qj_i}(v_{k,d}, v_{k,w})}} f(v_{k,d}) f(v_{k,w}) dv_{k,d} dv_{k,w} \quad (7)$$

The vector of unknown parameters can be estimated by maximizing the simulated log-likelihood function, i.e. by solving:

$$\max_{b_k, \sigma_{k1}, \sigma_{k2}} SLL(b_k, \sigma_{k1}, \sigma_{k2}) = \max_{b_k, \sigma_{k1}, \sigma_{k2}} \sum_{q=1}^Q \ln \frac{1}{R} \sum_{r=1}^R P_{qj,d,w}^r(b_k, \sigma_{k1}, \sigma_{k2}) \quad (8)$$

A specific code was written in Gauss to estimate this model. We used the Mixed Logit Estimation Routine for Panel Data developed by Train *et al.* (1999), that accounts for the correlation in the unobserved portion of the utility due to repeated measurements. This routine allows Halton draws (Bhat, 2001) for simulating the log-likelihood function in (8).

### 3. Dataset analysis

The Mobidrive panel dataset involved 160 households and 360 individuals in the main survey. Details about the data and their collection techniques can be found in Axhausen *et al.* (2002) and in PTV AG *et al.* (2000)<sup>5</sup>. The recorded days were structured according to activity chains on a daily basis and all trips were grouped into tours. Each tour had associated a main activity (i.e. work/education) for working days and a principal activity, which was defined as the longest duration out-of-home activity, for non-working days. All daily activity chains were represented in relation to these pivotal activities; the sequence of chains for a given day (week/individual) was called daily (weekly/individual) schedule. Most activity-based frameworks proposed in the literature and applied in practice (Bhat and Singh, 2000; Cirillo and Axhausen, 2006), are based on a sequence of tours. Several activities can be performed within each tour (main activity and secondary stops), but usually the mode remains the same within each tour. This is confirmed in our database where the same mode is used for all trips

<sup>5</sup> See also <http://www.ivt.ethz.ch/vpl/research/mobidrive> for a list of papers employing the Mobidrive data.



within a tour in more than 90% of the cases. A detailed description of the framework applied to the original Mobidrive survey to define tours can be found in Cirillo and Axhausen (2006).

As in Cherchi and Cirillo (2014), other than some further tests on the availability of alternatives, we concentrated only on week days, so our final sample consists of 4089 single tours, 2488 daily schedules, 674 weekly schedules, 129 individual schedules and 56 household schedules. Saturdays and Sundays were also excluded in line with the work of Schlich and Axhausen (2003) where weekend days were treated separately.

Other than the typical level-of-service attributes, several *SE* and other variables were available from the survey and, as we will show in the next section, resulted significant in model estimation. In particular, it is important to mention that we tested not only the linear effects of single *SE* attributes (such as age and so on) but also analysed some categories formed by combining *SE* characteristics (i.e. allowing for systematic taste variations, Ortúzar and Willumsen, 2011). In particular, the sample was composed mainly of non-workers (75%); however, among the workers, 23% worked full time and 20% of the part-time workers were females. Tours were equally distributed among work/study (35%), shop/leisure (35%) and other activities (30%), and almost all ages were represented, although the majority (one third of the sample) lied in the range 51 to 65 years, while youngsters accounted only for 10% (exactly 5% between 18 and 25, and another 5% between 25 and 35). On the other hand, 27% of the sample was married with children under 18 years old; 45% declared to be the main car user and, in line with this number, 39% of the tours in the sample were made as car driver.

Although public transport was used only for 15% of the tours in our sample, 33% of the individuals declared to have a seasonal ticket. Even more interesting is to note that 70% of the tours were single tours (i.e. without additional stops between the main origin and destination); 16% had one stop and only 14% had more than one stop. Even car drivers (notwithstanding the flexibility offered by the car) mainly did single tours (64%), although, as expected, they tended to do a higher number of stops (even four and five stops) than car passengers, pedestrians and public transport users.

Finally, it is important to note that our sample is evenly distributed over days of the week and over the six weeks of the panel. The characteristics of the tours are quite similar over the days and over the weeks, with few exceptions. As mentioned before, *Car Driver* is by far the most popular travel mode and its use is stable<sup>6</sup> over the days of the week and over the six weeks of the panel.

#### 4. Modelling results

Using the dataset described in the previous section, several models were estimated accounting, as much as possible, for systematic taste variations. Then, random heterogeneity in tastes for travel time and cost was also estimated and correlation among individuals over different time-periods explicitly analysed. Table 1 reports the results of several ML models estimated with different assumptions about correlation over observations. A simpler MNL allowing for systematic taste variations (parameterized effects) is also shown for comparison. Firstly, as expected, accounting for random heterogeneity, whatever the type of correlation considered, significantly improves model estimation. The MNL model estimated with an equivalent utility specification to the ML is inferior to any of the estimated ML models (the LR test allows rejecting the MNL at any significance level).

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<sup>6</sup> A tour is defined as “stable” if its characteristics (time, cost, purpose, mode, and so on) are equal to another tour already performed in a previous day (or in a previous period of the same day).

*Table 1 approximately here*

Before analysing the effect of correlation, note that the mean values of all parameters do not vary among the different correlation specifications. All parameters are significant (t-test rejected at more than 95% significance) with very few exceptions. We also found that there are seven significant systematic variations around the travel time variable and 16 *SE* attributes explaining systematic alternative specific preferences. In particular, we found that the marginal utility of travel time is lower for individuals who are married with children, for females working part time and for work trips. Conversely, the marginal utility of travel time increases (is smaller in absolute value) with the number of stops made during the tour (maybe because activities are performed at each stop). It is also smaller for those living in suburban locations and using *Public Transport* (the longer the trips the smaller the disutility of an extra minute travelling), for educational trips (students care less about travel time) and for bikers over 65 years old (as they are likely retired and they care less about travel time and probably feel also health benefits in biking). Interactions with the cost attribute were also tested but none was found significant.

As for the preferences for each alternative, it is not surprising that *Car Driver* is preferred by those who are mainly car-users and travel many miles. It is also not surprising that *Public Transport* is preferred by season ticket owners, while it is not liked for leisure trips, by older people or by those who have children. It is worth noting that variables such as miles travelled and possession of a season ticket are usual indicators of habit (Gärling and Axhausen, 2003).

It is also interesting to remark that the low level of significance of the mean value of the alternative specific constants (*ASC*) in all alternatives (except the *Bike*) is due precisely to the inclusion of systematic heterogeneity in preferences for specific alternatives; in the models estimated without the *SE* attributes the *ASC* were all extremely significant. As for the *Bike ASC*, we believe that preference for biking depends more on individual attitudes towards this specific mode than on the specific characteristic of the individual or mode, and so it deserves a different analysis that cannot be carried out with the data available.

Regarding the effect of correlation over individuals in panel data, as expected, models improved significantly as correlation was extended from the single day, to the week and to all tours performed in the six weeks (these results are not reported in Table 1). In a short survey panel individual correlation might be due to two different effects: correlation across the same day over the entire period (i.e. six weeks here) and correlation over different days of a given week. Separate analyses were performed to try and disentangle these two effects.

In particular, model ML1 (Panel-week) accounts for correlation across days of the same week but assumes that observations across weeks are independent. The ML2 model (Panel day-of-the-week) accounts for correlation across the same day in different weeks (i.e. across all tours made by the same individual on the six Mondays, the six Tuesdays, and so on), while observations belonging to different days of the same week are considered independent. As reported in Table 1, both models show significant random heterogeneity for the travel time and cost parameters and although not directly comparable, they only differ in the way correlation is accounted for. Thus, comparing their log-likelihoods at convergence suggests that, in our six-week panel data there is more correlation across a given day over the six weeks (ML1) than across different days of the same week (ML2). However, we cannot tell if both types of correlation do actually exist or if only one type is really important.

The specification adopted in equation (5) helps clarifying this issue. In fact, when both

correlations (across days of the same week and across a given day-of-the-week) are estimated jointly, as in model ML3 (Panel week&day), results show that correlation across days of the same week loses significance for both the parameters of travel time and cost.

It is important to mention that none of our models presented empirical identification problems. Different from the theoretical identification (Walker, 2002), which is inherent to the model specification regardless of the data at hand, the empirical identification depends only on the information used to estimate the model and can be revealed only during the estimation process. Following Chiou and Walker (2007), we checked if our results remained stable when increasing the number of draws in the estimation, this was an expected result as we are using panel data. As reported by Cherchi and Ortúzar (2008), empirical identification problems reduce considerably as the number of observations available for each individual increases. Notwithstanding, although we did not find empirical identification problems, we found that the correlation across days of the same week was highly sensitive to the seed used for the random draws. Instead, the correlation across a given day-of-the-week was always highly significant. This issue deserves further investigation.

Finally, we report in Table 2 the median values of Willingness to Pay (WTP) obtained with the four proposed model specifications. The multinomial logit model (MNL) clearly underestimates the average value of WTP and the WTP calculated for specific segments of the population for different trip types. The WTP obtained with the MNL is less than €7 per hour, while all panel specifications estimate WTP to be in the order of €20 per hour. Married individuals with children and individuals travelling to work have the highest WTP values probably because of their time constraints. As expected, students and female working part-time have lower WTP, as well as trips by public transport departing from suburban areas. These results attest that model structures that correctly account for the panel nature of the data not only produce better model fit, but also provide more reliable estimates of individual preferences and of the trade-off between relevant policy attributes.

## 5 Conclusions

The use of panel data has recently increased in the area of travel behaviour research. Nevertheless, applications mainly refer to time-use and activity choice and duration, while use of panels in mode choice modelling to better capture, for example, individual heterogeneity has received less attention. In particular, short survey panels are characterised by repeated measurements on the same sample of units gathered over a “continuous” period of time. This raises interesting issues, not yet explored, related with the several dimensions of correlation that might appear across responses provided by the same individual: over trips made in the same day, the same week, a given day-of-week, and/or over individuals and households.

In this paper, we specifically addressed the issue of the several dimensions of correlation in a short (six-week) survey panel. We estimated a random parameters Mixed Logit model accounting for correlation across individuals over two time-periods: a single week and a given day (i.e. Mondays) in the whole panel. We first analysed these effects separately, and then we tried to disentangle the relative effects of each type of correlation. The models also account for several types of systematic heterogeneity over individual preferences.

As expected, accounting for correlation over individuals in panel data improves enormously the model results. Not surprisingly, results improved significantly as we extended correlation from a single day, to a week, to all tours performed in the six-week period. However, more interestingly, we found that in our dataset, there is more correlation across the same day over

the six weeks than across different days of the same week. In particular, when both types of correlation were estimated jointly, the effect of correlation across different days of the same week disappeared and only correlation across the same day over the six weeks remained significant. When different models were estimated for each type of correlation, it was not possible to draw conclusions about the relative effect of correlation over different time-periods; in fact, it was not possible to ascertain whether only one type of correlation is indeed important or if both types of correlation do actually exist.

The specification adopted helps clarifying the true effect that correlation can have in short panel data. This is crucial to understand the long-term structure of individual choices, to correctly estimate models and to properly use them in prediction. Moreover, as we found that in our sample there is no variability across tours made on the same day over six weeks, this suggests that one week could be an appropriate length for estimating mode choice models and to correctly reveal such variability. Having more weeks, (i.e. a survey longer than one week) could be more important in terms of increasing the total number of observations and the number of observations for each individual (better statistical results).

Our results have also important policy implications. Capturing correctly the correlation over time-periods does not affect directly policy decisions, but improving model estimations indirectly provides forecasts that are more correct. This has a potentially huge impact in policy forecast and policy decisions as it might lead, for example, not to prioritize policies in favour of suburban areas or study trips, which are extremely relevant as found when correlation is correctly taken into account. Another important policy effect is that disregarding panel correlation (i.e. using the results from the MNL) would underestimate the impact of the number of stops in a tour, which has again a huge impact in the level of urban traffic. At the same time, our results clearly indicate that major variability in transport mode use occurs across days of the same week, probably due to the distribution of activities over the week. From a policy perspective, this result is important because it suggests the need to promote a mix of transport options that allow individuals to conveniently adapt to their heterogeneous transport needs over the week. This is in line with the findings of Heinen and Chatterjee (2015), who analysed individual-level variability in transport mode usage using continuous indicators.

Our analysis of mode choice was based on tours because the same mode was used for all trips within a tour in more than 90% of the cases in our dataset. However, there is also evidence that different modes might be used in trip chaining (e.g. Heinen and Chatterjee, 2015; Susilo and Axhausen, 2014). In this case, a distinction needs to be made whether an independent choice of mode is made at each trip (tour) of the chain or if the combination of modes is a unique choice made for the whole tour. This is an interesting issue that deserves to be studied further.

Finally, our model assumes that the decision about performing an activity at a given location is already made and that individuals just decide about the transport mode, but includes as independent variables travel time, purpose of the trip and time budget. If travel time increases due to congestion, the time budget for other activities will decrease and these two variables will affect the mode choice probabilities. Our model does not explicitly account for the strong link between activities and trips and for the fact that some activities might not be performed if the combination of activity-timing-location-mode is not right. However, it can be easily integrated into a tree decision structure (i.e. activity chain – location – mode choice).

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## References

- Arentze, T. and Timmermans, H. (2003) Modelling learning and adaptation processes in activity-travel choice. *Transportation* 30, 37-62.
- Susilo, Y.O and Axhausen, K.W (2014) Repetitions in individual daily activity-travel-location patterns: a study using the Herfindahl-Hirschman Index. *Transportation* 41, 995-1011.
- Axhausen, K.W., Zimmermann, A., Schönfelder, S., Rindsfuser, G. and Haupt, T. (2002) Observing the rhythms of daily life: a six-week travel diary. *Transportation* 29, 95-124.
- Bhat, C.R. and Singh, S.K. (2000) A comprehensive daily activity-travel generation model system for workers. *Transportation Research* 34A, 1-22.
- Bhat, C.R. (2001) Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model. *Transportation Research* 35B, 677-693.
- Börjesson, M., Cherchi E., and Bierlaire, M. (2013) Within individual variation in preferences: equity effects of congestion charges. *Transportation Research Record* 2382, 92-101.
- Cherchi, E. and Cirillo, C. (2008) A modal mixed logit choice model on panel data: accounting for systematic and random heterogeneity in preferences and tastes. 86<sup>th</sup> *Conference of the Transportation Research Board*. Washington D.C.
- Cherchi, E. and Ortúzar, J.de D. (2008) Empirical identification in the mixed logit model: analysing the effect of data richness. *Network and Spatial Economics* 8, 109-124.
- Cherchi E., Börjesson, M., and Bierlaire, M. (2013) A hybrid mode choice model to account for the dynamic effect of inertia over time. 3<sup>rd</sup> *International Choice Modelling Conference*, Sydney, Australia
- Cherchi, E. and Cirillo, C. (2014) Understanding variability, habit and the effect of long period activity plan in modal choices: a day-to-day, week-to-week analysis on panel data. *Transportation* 41, 1245-1262.
- Chiou, L. and Walker, J.L. (2007) Masking identification in the discrete choice model under simulation methods. *Journal of Econometrics* 141, 683-703.
- Cirillo, C. and Axhausen, K.W. (2006) Evidence on the distribution of values of travel time savings from a six-week travel diary. *Transportation Research* 40A, 444-457.
- Cirillo, C. and Axhausen, K.W. (2010) Dynamic model of activity type choice and scheduling. *Transportation* 37, 5-38.
- Copperman, R.B. and Bhat, C.R. (2007) An exploratory analysis of children's daily time-use and activity patterns using the child development supplement (CDS) to the US Panel Study of

Income Dynamics (PSID). *Transportation Research Record* 2021, 36-44.

Dharmowijoyo, D.B.E., Susilo, Y.O. and Karlström A. (2015) Collecting a multi-dimensional three-weeks household time-use and activity diary in the Bandung Metropolitan Area, Indonesia. *Transportation Research* 80A, 231-246.

Dharmowijoyo, D.B.E., Susilo, Y.O. and Karlström A. (2016) Day to day variability in travellers' activity travel patterns in the Jakarta Metropolitan Area. *Transportation* (in press).

Doherty, S.T. and Miller, E.J. (2000) A computerized household activity scheduling survey. *Transportation* 21, 75-97.

Gärling, T. and Axhausen, K.W. (2003) Introduction: habitual travel choice. *Transportation* 30, 1-11.

Greene, W.H. and Hensher, D.A. (2007) Heteroskedastic control for random coefficients and error components in mixed logit. *Transportation Research* 43E, 610-623.

Hanson, S. and Huff, J.O. (1988) Systematic variability in repetitious travel. *Transportation* 15, 111-135.

Heinen, E. and Chatterjee, K. (2015) The same mode again? An exploration of mode choice variability in Great Britain using the National Travel Survey. *Transportation Research* 78A, 266-282.

Jara-Díaz, S., Munizaga, M., Greeven, P. and Guerra, R (2007) The unified expanded goods-activities-travel model: theory and results. *11<sup>th</sup> World Conference on Transport Research*, Berkeley, California.

Khandker, M.N.H and Miller, E.J. (2007) Modelling activity program generation considering within day and day-to-day dynamics in activity travel behaviour. *86<sup>th</sup> Conference of the Transportation Research Board*, Washington D.C.

Minnen, J., Glorieux, I. and van Tienoven, T.P. (2015) Transportation habits: evidence from time diary data. *Transportation Research* 76A, 25-37

Minnen, J. and Glorieux, I., (2011) Two Days a week? A comparison of the quality of time-use data from 2-day, 7-day diaries and a weekly work grid. In Carrasco, J.A., Jara-Díaz, S. and Munizaga, M. (eds.), *Time Use Observatory*, 105–118. Grafica LOM, Santiago.

Muñoz, J.C., Ortúzar, J. de D. and Gschwender, A. (2009) Transantiago: the fall and rise of a radical public transport intervention. In W. Saaleh and G. Sammer (eds.), *Travel Demand Management and Road User Pricing: Success, Failure and Feasibility*, 151-172. Ashgate, Farnham.

Ortúzar, J. de D. and Willumsen, L.G. (2011) *Modelling Transport*. Fourth Edition, John Wiley and Sons, Chichester.

Pas, E.I. (1988) Weekly travel-activity behaviour. *Transportation* 15, 89-109.

Pas, E.I. and Sundar, S. (1995) Intra-personal variability in daily urban travel behaviour: some additional evidence. *Transportation* 22, 135-150.

PTV A.G., Fell, B., Schönfelder, S. and Axhausen, K.W. (2000) Mobidrive questionnaires. *Arbeitsberichte Verkehrs- und Raumplanung* 52, Institut für Verkehrsplanung, Transporttechnik, Strassen- und Eisenbahnbau, ETH Zürich.

Schlich, R. and Axhausen, K.W. (2003) Habitual travel behaviour: evidence from a six-week travel diary. *Transportation* 30, 113-36.

- Sillano, M. and Ortúzar, J. de D. (2005) Willingness-to-pay estimation with mixed logit models: some new evidence. *Environment and Planning* 37A, 525-550.
- Smart, H.E. (1984) The dynamics of change: applications of the panel technique to transportation surveys in Tyne and Wear. *Traffic Engineering and Control* 25, 595-598.
- Stopher, P.R., Clifford, E. and Montes, M. (2008) Variability of travel over multiple days. *87<sup>th</sup> Conference of the Transportation Research Board*, Washington D.C.
- Sunkanapalli, S., Pendyala, R. and Kuppam, A.R. (2000) Dynamic analysis of traveller attitudes and perceptions using panel data. *Transportation Research Record* 1718, 52-60.
- Train, K.E. (2009) *Discrete Choice Methods with Simulation*. Second Edition, Cambridge University Press, Cambridge.
- Train, K. and Sonnier, G. (2005) Mixed logit with bounded distributions of correlated partworths. In A. Alberini and R. Scarpa, (eds.), *Applications of Simulations Methods in Environmental Resource Economics*, Chapter 7. Kluwer Academics Publisher, Dordrecht.
- Train, K., Revelt, D. and Ruud P. (1999) Mixed logit estimation routine for panel data. <http://eml.berkeley.edu/Software/abstracts/train0296.html>.
- Vanhulsel, M., Janssens, D. and Wets, G. (2007) Calibrating a new reinforcement learning mechanism for modelling dynamic activity-travel behaviour and key events. *86<sup>th</sup> Conference of the Transportation Research Board*, Washington DC.
- Vij, A. (2013) *Incorporating the Influence of Latent Modal Preferences in Travel Demand Models*. Ph.D. Thesis, Department of Civil and Environmental Engineering, University of California at Berkeley.
- Walker, J. (2002) The mixed logit (or logit kernel) model: dispelling misconceptions of identification. *Transportation Research Record* 1805, 86-98.
- Yañez, M.F., Cherchi, E., Heydecker, B.G. and Ortúzar, J. de D. (2008) On the treatment of repeated observations in panel data: efficiency of mixed logit parameter estimates. *XV Panamerican Conference on Traffic and Transport Engineering*. Cartagena de Indias.
- Yañez, M.F., Mansilla, P. and Ortúzar, J. de D. (2010) The Santiago Panel: measuring the effects of implementing Transantiago. *Transportation* 37, 125-149.

Table 1 – Model results: Correlation over days and weeks in panel data

		MNL		ML1 Panel-week		ML2 Panel days of week		ML3 Panel-week&day	
Variable	Alts.	Estimate	t-test	Estimate	t-test	Estimate	t-test	Estimate	t-test
ASC_Car Pass	CP	0.1268	0.51	0.3685	0.74	0.4032	0.84	0.3934	0.80
ASC_PT	PT	-0.8676	-2.80	-0.7840	-0.95	-0.5368	-0.72	-0.5780	-0.76
ASC_Walk	Walk	-0.0306	-0.12	0.7118	1.10	0.7881	1.31	0.7573	1.23
ASC_Bike	Bike	-1.5992	-6.26	-1.5566	-2.30	-1.4557	-2.23	-1.4782	-2.22
Time (mean)	All	-0.0196	-5.20	-0.0637	-5.52	-0.0698	-6.52	-0.0707	-6.54
Time (s.d)	All					-0.0779	-9.50	-0.0732	-5.56
Corr. day-weeks									
Time (s.d)	All			-0.0711	-8.69			-0.0055	-0.55
Corr. weeks									
Cost (mean)	All	-0.0866	-5.09	-0.0870	-2.30	-0.1092	-2.57	-0.1127	-2.81
Cost (s.d)	All					0.1197	3.86	0.1027	2.66
Corr. day-weeks									
Cost (s.d)	All			0.0946	3.08			0.0669	1.28
Corr. weeks									
Time*Marchild	All	-0.0199	-4.42	-0.0292	-1.63	-0.0316	-3.72	-0.0308	-3.54
Time*Work	All	-0.0218	-4.26	-0.0205	-1.19	-0.0131	-0.96	-0.0135	-1.02
Time*FemPartTime	All	-0.0169	-3.05	0.0013	0.09	0.0001	0.01	-0.0001	-0.01
Time*Nstop	All	0.0056	3.18	0.0137	3.17	0.0150	3.21	0.0152	3.42
Time*Education	All	0.0142	3.69	0.0174	1.69	0.0190	1.98	0.0191	2.00
Time*Sub-urb. loc.	PT	0.0178	4.93	0.0341	3.05	0.0337	3.32	0.0340	3.37
Time*age65	B	0.9246	4.17	1.3667	2.43	1.4067	2.53	1.4112	2.54
Age 26-35	CD	2.2000	4.57	2.6764	2.87	2.6000	2.79	2.5697	2.76
Age 51-65	W	0.7455	5.03	0.9512	1.48	1.0772	2.37	1.0750	2.32
Age 18-25	B	-0.0255	-4.03	-0.0335	-2.09	-0.0353	-2.17	-0.0354	-2.19
Age 26-35	B	1.0874	5.23	1.3184	1.86	1.3150	1.85	1.3104	1.84
Age 51-65	B	1.8072	5.17	2.5028	2.89	2.4002	2.69	2.3832	2.73
Age 51-65	PT	-0.4435	-2.88	-0.1309	-0.31	-0.1556	-0.35	-0.1615	-0.37
Main car user	CD	1.4406	11.8	1.6704	4.27	1.7040	4.65	1.6987	4.55
Annual Mileage	CD	0.0178	5.04	0.0149	1.51	0.0159	1.65	0.0158	1.64
Urban location	PT	0.8664	4.24	1.2712	2.26	1.2766	2.50	1.3012	2.56
Marchild	PT	-1.3499	-7.98	-1.6296	-3.55	-1.6747	-3.57	-1.6859	-3.61
SeasonTicket	PT	2.0320	11.1	1.6597	3.36	1.5764	3.24	1.5821	3.21
Leisure	PT	-0.7429	-3.31	-0.9224	-2.56	-0.8895	-2.57	-0.8611	-2.52
Leisure	CP	1.0798	5.91	1.0951	3.07	1.0842	3.10	1.0893	3.11
Work	PT	1.3938	7.57	1.5670	2.62	1.4906	2.65	1.5328	2.74
Time Budget	CD	0.0010	3.65	0.0012	2.55	0.0013	2.80	0.0012	2.73
Time Budget	B	0.0015	7.10	0.0018	3.28	0.0018	3.22	0.0018	3.19
$l(\theta)$		-2765.35		-2519.68		-2502.78		-2501.07	
$\rho^2(C)$		0.2055		0.2760		0.2809		0.2814	

**Legend:**

CD = Car Driver; CP = Car Passenger; PT = Public Transport; W = Walk; B = Bike;

Time [min]; Cost [DM] including any parking fees

Age 18–25/age 26–35/age 51–65/age&gt;65: (Dummy)

FemPartTime = 1, if female and employed part-time

Marchild = 1, if married with children under 18

Sub-urb. loc. = if the origin of the tour is in a suburban location

Nstop is the number of secondary activities observed within each tour (Discrete)

M\_CAR\_U = 1 if main car user

P\_A\_MVT is the Total annual mileage by car (Continuous)

SeasonTicket = Number of season tickets (Discrete)

Education = 1, if the purpose of the main activity of the tour is study

Leisure = 1, if the purpose of the main activity of the tour is leisure

Work = 1, if the purpose of the main activity of the tour is work

Time budget [min] is the time spent on previous activities (home stay included) and previous travel



Table 2: Estimated willingness to pay

		<b>MNL</b>	<b>ML1 Panel-week</b>	<b>ML2 Panel days of week</b>	<b>ML3 Panel-week&amp;day</b>
WTP <sup>(*)</sup>		6.79	21.97	19.18	18.82
X Marchild	All	13.68	32.03	27.86	27.02
X Work	All	14.34	29.03	22.78	22.41
X FemPartTime	All	12.65	21.52	19.15	18.85
X Nstop	All	4.85	17.24	15.05	14.78
X Education	All	1.87	15.97	13.96	13.74
X Sub-urb. loc.	PT	0.62	10.21	9.92	9.77

(\*) Values are in €/hour (1 Deutsche Mark = 0.5 Euros)